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TYPICAL PROBLEMS AND INTELLIGENT RECOGNITION OF FLUE GAS CONTINUOUS EMISSIONS MONITORING

The continuous emissions monitoring system (CEMS) data of flue gas serves as a critical metric for determining whether exhaust emissions comply with regulatory standards. 10 typical issues within the CEMS for flue gas, categorized into three groups: installation of sampling devices; system parameter settings; and operations and equipment maintenance, are investigated. Measures to address these issues, including the daily maintenance, historical data analysis, completion of operation and maintenance records, and comparative validation of CEMS results, are explored. Furthermore, the integration of intelligent analysis techniques into CEMS data interpretation, electricity analysis, and video surveillance anomaly detection is examined.

1. INTRODUCTION

Continuous emissions monitoring system (CEMS) of pollution sources provides real-time data, representing a critical direction in the digital and intelligent development of environmental monitoring. It also serves as an essential method for non-site supervision and has gained widespread application [1]. In 2023, non-site inspections nationwide involved over 53,000 personnel in China. The *Implementation Opinions on Accelerating the Establishment of a Modernized Ecological and Environmental Monitoring System*, issued by the Ministry of Ecology and Environment in 2024, emphasized the need to solidify the foundation of high-quality monitoring data and strengthen efficient monitoring management, thereby raising the requirements for monitoring data quality and enhancing regulatory oversight of monitoring activities.

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Flue gas CEMS has emerged as a focal point in environmental inspections conducted at various levels. Over the past few years, many issues have been identified within enterprises, including abnormal operation of continuous monitoring facilities and instances of data falsification [2]. However, assessing compliance with emission standards alone is insufficient to provide a comprehensive evaluation of the performance of pollution control facilities, CEMS data can be further leveraged to more accurately assess the pollution emission levels of installations [3, 4].

Pollutant discharging entities are required to take on primary responsibility for pollution monitoring and to ensure the authenticity and accuracy of CEMS data from fixed pollution sources. Given the technical complexity associated with continuous monitoring, many polluting entities often outsource flue gas continuous emissions monitoring to third-party professional maintenance organizations. In some cases, entities have resorted to data falsification in an attempt to evade penalties for exceeding pollution discharge standards.

Recent efforts by environmental regulatory authorities have primarily concentrated on non-site supervision of CEMS. Several provinces and municipalities, including Tianjin, Hebei, and Jiangsu, have pioneered the use of sub-metering electricity monitoring as a regulatory tool, thereby developing dynamic management approaches for automated pollution source monitoring. Despite these advancements, significant gaps remain in the current research landscape. Future studies should focus on empowering pollutant discharging entities to independently identify issues across the entire process of flue gas continuous emissions monitoring. Additionally, there is a pressing need to explore the application of advanced technologies, such as machine learning, in the intelligent analysis of flue gas pollution source monitoring. Furthermore, research should address necessary improvements in the operation and maintenance of continuous emissions monitoring systems to enhance their reliability and accuracy [5–8].

2. METHODS

2.1. ANALYSIS OF TYPICAL ISSUES IN FLUE GAS CONTINUOUS EMISSIONS MONITORING SYSTEMS

In CEMS for stationary pollution sources, the primary pollutants monitored include sulfur dioxide (SO_2), nitrogen oxides (NO_x), and particulate matter (PM). Additionally, ancillary parameters such as flue gas temperature, pressure, flow velocity, oxygen content, and humidity are concurrently measured to provide a comprehensive assessment of emission characteristics. The regulatory frameworks governing these systems are established by the *Specifications for Continuous Emissions Monitoring of* SO_2*,* NO_x*, and Particulate Matter in Flue Gas from Stationary Sources* (HJ 75-2017) and the *Specifications and Test Procedures for Continuous Emission Monitoring Systems for* SO_2*,* NO_x*, and Particulate Matter in Flue Gas from Stationary Sources* (HJ 76-2017).

The workflow of flue gas continuous emissions monitoring involves several critical stages, including the installation of sampling devices, configuration of system parameters, operation of continuous emissions monitoring, and routine maintenance of monitoring equipment. The challenges encountered during these processes are multifaceted and have been systematically summarized in Table 1 [7].

Table 1

Identification and analysis of typical challenges in CEMS

No.	Category	Specific isues
1	Improper facility setup	failure to comply with permit requirements for CEMS setup; non-standard placement of sampling locations; irregular routing of sampling lines
2	Data falsification	establishment of bypass emission routes; interference with sampling processes; disruption of production conditions
3		electronic interference; tampering with monitoring data; insufficient data collection frequency; inadequate data transmission rates; false marking of power outages or disconnections of sampling lines; intentional mislabeling of exceedances as non-normal operating conditions
4		alteration of data conversion equations; modification of zero-point calibration parameters; adjustment of range settings; changes to flue cross-sectional area parameters
5		Obstruction or deliberate rotation of surveillance cameras
6	Improper operation and maintenance	CEMS not undergoing acceptance procedures
7		malfunctioning flue gas heating and condensation systems; blocked sampling probes; leaking sampling lines
8		insufficient types or concentrations of standard gases; expired standard gases
9		delayed calibration; untimely maintenance activities such as filter core cleaning and replacement; non-standard record-keeping for operation and maintenance
10		delayed comparative monitoring; failure to conduct manual monitoring during equipment malfunctions

After the CEMS for stationary pollution sources connected to the network, compliance with HJ 75-2017 requires the verification of key performance indicators, including:

- zero drift and span drift of monitored factors,
- indication error,
- system response time,
- measurement accuracy of flue gas flow velocity, temperature, and humidity.

Additionally, the following installation and operational specifications must be adhered to:

- sampling location selection:

– Avoid abrupt flow disturbances, such as bends or cross-sectional variations.

– The sampling point should be positioned ≥ 4 times the pipe diameter downstream from bends, valves, or diameter changes, and ≥ 2 times the pipe diameter upstream.

- Extractive sampling line requirements:

– The entire sampling line should maintain a downward slope of > 5° to prevent condensation.

– Heating insulation must be applied at ≥ 120 °C or 10 °C above the flue gas dew point temperature to avoid moisture interference.

This ensures measurement accuracy and long-term system reliability in compliance with regulatory standards.

During the production phase, it is imperative to inspect for the presence of bypass emission outlets and to ensure that all exhaust gases are treated and discharged exclusively through legally designated emission outlets. In the sampling phase, the sampling port and its surrounding area must be free from artificial obstructions, such as shading or spraying, which could potentially interfere with the sampling process. Moreover, the integrity of the samples must be rigorously maintained; practices such as sample replacement, dilution, adsorption, or filtration, which could alter the nature of the monitoring samples, are strictly prohibited. During the monitoring process, the normal production and pollution control operations of the polluting entity must be maintained, and temporary measures such as ammonia spraying to interfere with CEMS are strictly forbidden. For flue gas CEMS, it is essential to ensure that there is no intentional electronic interference with the operation of the monitoring instruments, thereby guaranteeing the effective collection and transmission of CEMS data. Additionally, it is necessary to conduct thorough checks for the presence of any implanted software that could automatically or manually tamper with or fabricate monitoring data. The alteration or destruction of historical monitoring data and original records is strictly prohibited.

2.2. ROUTINE MAINTENANCE OF EQUIPMENT

The accuracy of monitoring results is intrinsically linked to the routine maintenance of CEMS. The timeliness and effectiveness of maintenance activities have emerged as a critical focal point during environmental inspections at all levels. Pollutant discharging entities are held accountable for ensuring the authenticity and accuracy of CEMS data, thereby bearing the primary responsibility for maintaining the integrity of the monitoring process.

Regarding the CEMS, several key aspects warrant attention. First, the normalcy of the sampling flow rate should be verified. Second, the condition of the particulate matter probe should be assessed to determine whether cleaning is required. Finally, the configuration and operational status of the sampling lines, condensing lines, and heating lines must be examined to ensure compliance with regulatory standards and optimal functionality.

If flue gas CEMS encounters a malfunction and is unable to operate normally for an extended duration, the polluting entity is required to immediately notify the competent environmental protection administrative authority. To ensure continuous monitoring during such periods, manual monitoring should be conducted in accordance with regulatory requirements. Specifically, manual monitoring must be performed no fewer than 4 times per day, with intervals between measurements not exceeding 6 hours. Comprehensive records of these manual monitoring activities must be meticulously maintained to ensure the validity and reliability of the monitoring data. The results of the manual monitoring should be promptly reported to the relevant authorities, serving as a temporary substitute to ensure the continuity and integrity of the monitoring process until the continuous monitoring equipment is restored to normal operation.

2.3. HISTORICAL DATA ANALYSIS

Leveraging historical data from 19,032 flue gas CEMS, researchers established an industrial flue gas emission database to calculate industrial emission factors and quantify emission volumes. Their analysis achieved a prediction uncertainty range of ±4% for SO_2 and NO_x emissions [9]. In the context of flue gas monitoring analysis models, several machine learning methods are frequently employed, including reinforcement learning (RL), artificial neural networks (ANN), and support vector machines (SVM), as detailed in Table 2 [10–12].

Table 2

Common methods and characteristics of continuous emissions monitoring and predicting

Method	Features	Applications
RL	enables the model to make decisions by altering experimental settings and learning from errors, thereby optimizing outcomes through iterative maximization of the reward function	suitable for process control under conditions of uncertainty; attention must be paid to the quality of the reward function
ANN	simulates adaptive learning processes akin to the human brain through hierarchical node connections; includes types such as feedforward, recurrent, convolutional, and long short-term memory neural networks	the reliability of the method is highly dependent on the quality of input process data; it can be utilized to predict pollutant emissions based on historical process and pollution data
SVM	constructs a hyperplane to effectively separate data points of different categories by learning from sample data and solving linear equations to identify the optimal classification hyperplane	suitable for real-time prediction and evaluation of continuous emissions, such as NO_x; requires high-quality datasets

During the operation and maintenance phase of CEMS, it is crucial to meticulously review and analyze historical monitoring data to detect any anomalies. Special attention should be given to data that remain static over extended periods or exhibit minimal fluctuations. Typically, the concentrations of pollutants in flue gas are expected to vary in response to changes in production conditions. However, if the data display an unreasonably regular pattern of fluctuation, such as periodic variations within a specific range, further investigation into the underlying causes is necessary.

A comparative analysis of CEMS data from different flue gas emission outlets within the same facility, which share identical production processes, can also reveal potential issues. For instance, if the monitoring data from one particular outlet consistently show significantly lower values or periodic fluctuations compared to others, this may indicate a problem. Research has demonstrated that such discrepancies can be attributed to insufficient heating temperatures in the heated sampling lines, leading to the formation of condensation within the sampling lines and subsequent blockages [13].

When production loads undergo significant changes, such as fluctuations in output or the start-up and shutdown of equipment, the concentrations of pollutants typically exhibit corresponding variations. This relationship is particularly evident in enterprises where production processes and operational workflows are closely monitored. For facilities equipped with flue gas desulfurization and denitrification systems, several auxiliary indicators can provide valuable insights. These include the usage records of desulfurization and denitrification agents, changes in the level of reagent storage tanks, variations in flue gas temperature, and the consumption of alkali solution in scrubbing towers [14].

When substantial changes in production conditions are observed but the monitoring data fail to reflect a reasonable response, further investigation is essential. This involves verifying whether continuous monitoring comparisons are conducted in a timely manner, assessing the accuracy of the comparison results, and confirming whether the parameters of the CEMS are correctly set according to the registered values.

2.4. COMPARISON AND VALIDATION OF CEMS

To enhance the accuracy of CEMS results and reduce uncertainties associated with reference methods, regular comparative monitoring should be conducted using reference methods that are specifically tailored to the characteristics of the industry's flue gas and its operational conditions. For SO_2 continuous monitoring, several reference methods are available, including portable ultraviolet (UV) absorption, potentiostatic electrolysis, and non-dispersive infrared (NDIR) absorption. Each method has specific application conditions that must be carefully considered. For example, high humidity during testing with the portable UV absorption method can cause SO_2 to dissolve in condensation water, resulting in test results that are lower than the actual values. When using this method, it is essential to heat the sampling tube and gas conduit or to implement rapid dehumidification measures. When employing the potentiostatic electrolysis method, potential interference from components such as carbon monoxide in the flue gas must be carefully managed [15, 16].

During comparative monitoring, it is crucial to ensure that both the CEMS and manual monitoring equipment, as well as the production conditions within the facility, are functioning normally. This involves inspecting the sampling probe, heated sampling lines, and pre-treatment system for any blockages or leaks. The stability of the CEMS sampling system, analysis system, and data transmission system should be verified. The parameters of the CEMS should be consistent with those used during system validation. Any leaks in the sampling lines that could lead to the loss of ambient air and an artificially elevated oxygen measurement should be identified and rectified [16].

3. RESULTS

To elevate the compliance management of flue gas emissions within pollutant discharging entities, the integration of flue gas CEMS capabilities into the internal environmental or production management information systems is recommended. This integration enables comprehensive analysis of flue gas CEMS data, production-related data, and video surveillance footage. Through this multifaceted approach, potential discrepancies and issues can be swiftly detected, thereby facilitating the implementation of targeted corrective measures. This strategy ultimately ensures the authenticity and accuracy of flue gas CEMS data, so that bolsters overall compliance and environmental stewardship.

3.1. INTELLIGENT ANALYSIS OF FLUE GAS CEMS DATA

Utilizing mathematical models to perform continuous analysis of the CEMS process can further enhance the efficiency with which polluting entities identify and address issues in flue gas continuous monitoring. The system framework for continuous monitoring is depicted in Fig. 1.

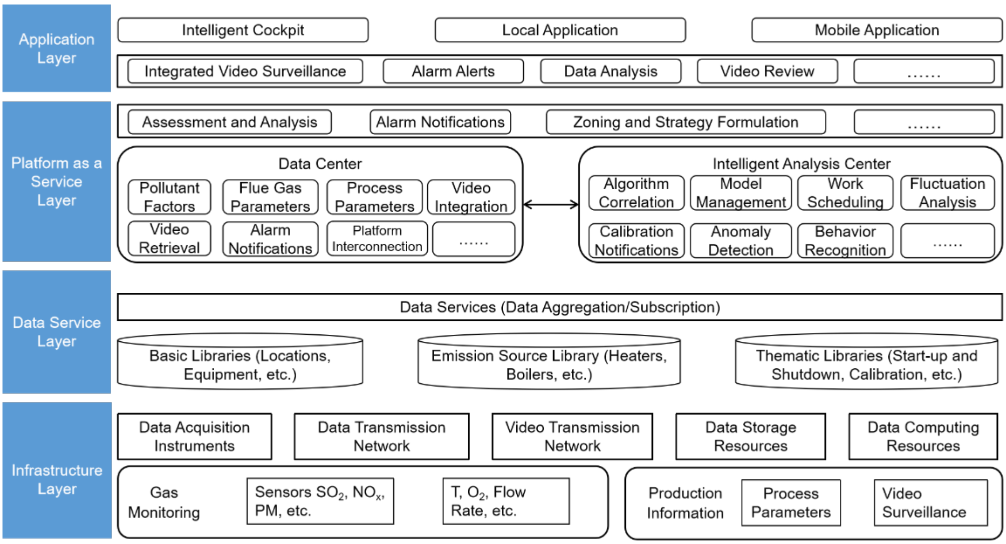

Fig. 1. Schematic diagram of a continuous emissions monitoring system for key polluting companies

Several key monitoring and alarm functionalities can be developed to enhance the operational oversight and compliance of flue gas monitoring systems:

- Hourly average concentration exceedance: detecting whether the hourly average concentrations of flue gas pollutants surpass regulatory thresholds.
- Anomalies in flue gas parameters: identifying abnormal readings in critical flue gas parameters, including temperature, pressure, flow rate, and oxygen content.
- Communication integrity of CEMS: ensuring the continuous and reliable communication status of the monitoring system to prevent data loss.
- Data transmission efficiency: verifying that the effective transmission rate of CEMS data achieves a minimum of 90%.
- Regulatory compliance of data marking: confirming that CEMS data are accurately and appropriately marked in accordance with regulatory requirements.
- Modification of critical monitoring equipment parameters: alerting when key parameters of the monitoring equipment are modified without authorization.
- Unusual data patterns: recognizing prolonged periods of constant values or abnormal fluctuations in monitoring data, which may indicate potential issues.

These functionalities provide real-time insights and enable prompt corrective actions, thereby enhancing the reliability, accuracy, and compliance of flue gas CEMS.

Pollutant discharging entities can leverage flue gas CEMS data to develop intelligent monitoring and early warning models. These models are based on historical data and process parameters such as fuel consumption, temperature, and flue gas flow rate. Machine learning algorithms, including RL, ANN, and SVR, can be employed to construct these models. Accurate and reliable monitoring data are essential for the development of effective machine learning models. However, it is important to strike a balance between model complexity and accuracy, as overly complex models may be prone to overfitting.

In a specific case study, nine neural network prediction models were trained using 12,086 instances and subsequently tested on 3,020 cases. These models utilized eight process parameters – generator output power, fuel gas temperature, fuel gas flow rate, exhaust gas temperature, flue gas O_2 content, flue gas heat balance, turbine rotational speed, and compressor air temperature – to predict NO_x emissions from a gas-fired power plant. The difference between the actual and predicted NO_x emission values was a mere 0.14% [12].

3.2. ANALYSIS OF PRODUCTION ELECTRICITY USAGE AND POLLUTION CONTROL

By leveraging data on electricity consumption from production facilities and exhaust gas treatment facilities, as well as pollutant emissions, pollutant discharging entities can establish industry-specific models that correlate exhaust gas emissions with electricity coefficients. Alternatively, machine learning methods can be employed to estimate pollutant emissions. Additionally, by analyzing the daily peak and trough characteristics of electricity usage, clustering feature models can be constructed to conduct outlier analysis. This serves as a supplementary tool to flue gas continuous monitoring. However, it is crucial to account for errors arising from non-production electricity consumption [17, 18].

In 2021, the Environmental Engineering Assessment Center of the Ministry of Ecology and Environment developed the *Technical Guidelines for Electricity (Energy) Monitoring Systems of Production Facilities and Pollution Control Facilities of Polluting Entities (Draft for Comments)*. These guidelines provide methods for assessing the operational status of pollution control measures. Key equipment for electricity monitoring related to flue gas desulfurization, denitrification, and dust removal facilities includes desulfurization fans, absorber tower circulation pumps, slurry circulation pumps, dilution fans, water pumps, denitrification fans, baghouse dust collector fans, and electrostatic precipitators.

Utilizing a feedforward neural network approach based on historical production electricity usage and flue gas parameters of enterprises, a model correlating electricity load with pollutant emissions can be constructed to predict NO_x and SO_2 emissions in flue gas, as depicted in Fig. 2.

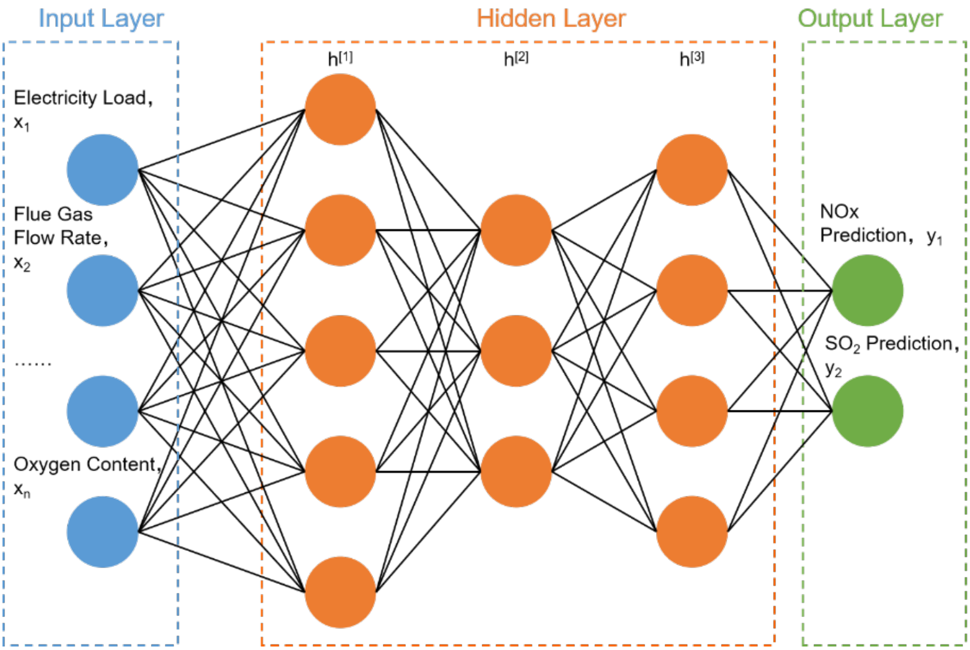

Fig. 2. Schematic diagram of a feedforward neural network for emission prediction

By examining changes in CEMS data, comparing electricity consumption before and during heavy pollution weather emergency responses, and contrasting electricity usage during production halts, it is possible to assess the operation of pollution control equipment. This approach can verify whether enterprises have implemented emergency emission reduction measures as stipulated and identify any unauthorized production during shutdown periods [7]. For example, during emergency response periods, steel and coking enterprises are expected to experience a reduction in electricity consumption due to production and emission limitations. In contrast, refineries and petrochemical enterprises may exhibit less pronounced changes in electricity usage. For casting enterprises, a mathematical model based on statistical regression of electricity and pollutant emission data has been developed to predict particulate matter emissions, with prediction errors ranging from –17.09 to 24.12% compared to actual measurements [19].

Monitoring electricity consumption can also indicate whether pollution discharging control facilities are operating normally, thereby assisting in determining whether abnormal conditions flagged in CEMS data are accurately marked. Furthermore, electricity consumption data can serve as a basis for identifying potential data falsification, such as intentional disconnection of power to continuous monitoring equipment or severing of sampling lines, and the improper marking of monitoring data as indicative of a production halt.

3.3. INTELLIGENT RECOGNITION OF ABNORMAL BEHAVIORS IN SURVEILLANCE VIDEOS

Video surveillance systems can capture and retain detailed records of personnel activities during the operation and maintenance (O&M) of CEMS. Specifically, surveillance cameras strategically placed in flue gas continuous monitoring stations, throughout the factory premises, near flue gas emission outlets, and at flue gas sampling ports can provide critical visual data. By leveraging machine learning algorithms to analyze these surveillance videos, it is possible to ensure that the O&M processes of CEMS are conducted in strict compliance with regulatory standards and with full transparency, as illustrated in Table 3 [20].

By utilizing surveillance videos, artificial intelligence-based visual recognition and analysis can be employed to monitor and analyze the behavior of personnel within the monitoring station. This approach enables the detection of specific actions, such as deliberately obstructing cameras, adjusting continuous monitoring equipment, altering system parameters, or cutting off power to the CEMS. Through the classification and identification of abnormal human behavior characteristics, these features can be systematically identified, extracted, and expressed to develop a robust behavior recognition model. Utilizing machine learning algorithms, the model can undergo deep learning to establish a comprehensive database of abnormal behavior actions within the flue gas monitoring station. This database serves as the foundation for training the intelligent recognition model, enabling real-time detection and identification of abnormal behaviors in the video. When potential abnormal actions are detected, the system can trigger an alert to notify relevant personnel.

Surveillance cameras positioned outside the monitoring station can be combined with automated video recognition technology to enhance monitoring capabilities. For instance, at flue gas emission outlets, the system can automatically capture images and trigger timely alarms when anomalies in the color or flow rate of the emitted flue gas are detected [21]. Similarly, if video surveillance is installed around flue gas sampling ports within the factory premises, it can be used to monitor the on-site sampling activities of third-party monitoring personnel. Machine learning models and algorithms can be developed and trained to detect and issue alerts for any abnormal behaviors, such as disconnecting sampling lines or replacing samples during the sampling process.

Table 3

Video surveillance scenarios and key points of visual recognition

Location	Scenario	Key points
Inside monitoring station	unauthorized personnel entering the operation area	facial recognition; behavior trajectory tracking; recording the identity and operation time of personnel
	manual modification of equipment parameters or calibration data	capturing screen operations such as keyboard input and abnormal frequency of mouse clicks; identifying analyzer panel status, such as the screen obstruction and abnormal button triggering
	obstructing/adjusting monitoring equipment or cameras	detecting camera obstruction; identifying abnormal equipment status, such as blurry camera images and angle deviations
	adjusting sampling probe position or diluting sampling gas	comparing with preset installation positions to monitor sampling probe position offsets; identifying abnormal pipeline connections such as unauthorized connections to dilution air lines
Flue gas emission outlet	abnormal flue gas emissions	identifying the time, color, and shape of smoke emissions to assist in judging treatment effectiveness and emission flow
	sampling probe status	identifying abnormal material adhesion or temperature fluctuations near the sampling port
	sampling lines	identifying abnormal pipeline layouts to determine bypass settings, changes in pipeline direction, or installation of dilution devices
	condenser/filter status	identifying abnormal condenser liquid accumulation and signs of filter removal

4. DISCUSSION AND CONCLUSIONS

In future efforts, the exploration of more intelligent applications in flue gas CEMS is warranted. Specific strategies include:

Integrating flue gas CEMS with production electricity analysis and intelligent recognition of surveillance videos through comprehensive planning and deployment. This integration aims to achieve timely alarms and early warnings in the continuous emissions monitoring process.

Developing intelligent flue gas CEMS platforms that can be seamlessly integrated into the information systems related to the production processes of pollutant-discharging entities. This integration will facilitate coordinated online and offline supervision throughout the entire process, from pollution-generating facilities to pollution control equipment and ultimately to pollution emission outlets.

Establishing a technical chain that encompasses flue gas pollution source CEMS databases, data quality control, intelligent data analysis models, and flue gas exceedance early warning systems. This chain will form a dynamic management and control system for flue gas treatment facilities, leveraging digital and intelligent technologies to enhance their functionality.

Continuous emissions monitoring of pollution sources represents a crucial method for environmental protection administrative authorities to conduct non-site inspections. Pollutant discharging entities are required to assume primary responsibility for continuous emissions monitoring. This includes gaining an in-depth understanding of the typical issues encountered during the continuous emissions monitoring of flue gas pollution sources and their underlying causes, as well as devising corresponding solutions. Additionally, these entities should enhance the maintenance of flue gas continuous emissions monitoring systems during routine production activities and ensure the quality of CEMS data through regular historical data analysis and comparative validation of CEMS data. Ultimately, this approach will promote the high-quality participation of enterprises in the construction of a beautiful China.

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